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Predicting the probability of target detection in static infrared and visual scenes using the fuzzy logic approach

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key words: fuzzy logic, target acquisition, signal detection theory, vision

ABSTRACT

The probability of detection (Pd) of targets in static infrared and visually cluttered scenes is computed using the Fuzzy Logic Approach (FLA). The FLA is presented as a robust method for the computation and prediction of the Pd of targets in cluttered scenes. The Mamdani/Assilian, and Sugeno Neurofuzzy-based models have been investigated. A large set of infrared (IR) imagery and a limited set of visual imagery has been used to model the relationships between several input parameters; the contrast, camouflage condition, range, aspect, width, and experimental Pd. The fuzzy and neuro-fuzzy models gave predicted Pd values that had 0.98 correlation to the experimental Pd's. The results obtained indicate the robustness of the fuzzy-based modeling techniques and the applicability of the FLA to those types of problems having to do with the modeling of human-in-the-loop target detection in any spectral regime.

1. INTRODUCTION

More than three decades ago Prof. L. A. Zadeh proposed the concept of fuzzy logic [1]. Following Mamdani and Assilian's seminal work in applying the fuzzy logic to the control of a steam engine in 1974 [2], the FLA has been finding a rapidly growing number of applications throughout industry and science. These applications include, transportation (subways, helicopters, elevators, traffic control, and air control for highway tunnels), automobiles (engines, brakes, transmission, and

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cruise control systems), washing machines, vacuum cleaners, rice cookers, VCRs, air conditioners, microwave ovens, video cameras, and other industries including steel, chemical, aerospace, medical diagnosis systems, information technology, and data analysis, ...etc. [3, 4, 5, 6, 7].

A strong point of the FLA is that it permits the encoding of expert knowledge directly and easily using rules with linguistic labels. A week point is that it usually takes some time to design and tune the membership functions which quantitatively define these linguistic parameters of interest. It has been found that artificial neural network learning techniques can automate this process and substantially reduce development time while improving performance. To enable a system to deal with cognitive uncertainties in a manner more like humans, researchers have incorporated the concept of fuzzy logic into these systems using a neural network approach. The integration of these two techniques is the Neuro-Fuzzy Approach (NFA) [8]. The NFA has potential to capture the benefits of both the fuzzy and the neural network methods in a single model.[1] Neuro-Fuzzy modeling basics and techniques will not be addressed in this paper, but will be discussed in a later paper. A new approach to the computation of the probability of target detection in infrared and visual scenes containing clutter is presented here. At present, target acquisition models, based on the theory of signal detection theory, are not mature enough to robustly model the human detection of targets in cluttered scenes. This is because our understanding of the visual world is a result of the perception, not merely detection, of the spatio-temporal, spectra-photometric stimuli that is transmitted onto the photoreceptors on the retina [8]. The computational processes involved with perceptual vision can be considered as the process of linking generalized ideas or concepts to retinal, early vision data [9]. These ideas or concepts may be represented in software using various clutter or edge metrics [10] as well as luminance attributes of a military vehicle or automobile. From a system theoretic point of view, human perceptual vision involves the mapping of early vision data onto one or more concepts, and then inferring a meaning of the stimuli based on prior experience and knowledge. The approaches of fuzzy and neuro-fuzzy systems provide a robust alternative to complex semi-empirical models for predicting observer responses to visual and IR cluttered scenes. The fuzzy-based approaches have been used to calculate the probability of detection (Pd) of vehicles in different infrared and visual scenes.

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2. PROBABILITY OF DETECTION (Pd) FOR GROUND TARGETS

During the past three decades there has been an increasing interest in the development and use of computational models to compute the static and dynamic probability of detection of a target in visual and infrared images that include a known or unknown amount of clutter [10,11,12,13]. Clutter and the idea of the probability of detection play a very important role in the area of machine vision and human-in-the-loop target acquisition.

The problem of modeling electro-optical (EO) systems for the purpose of ground vehicle countermeasures development and system performance modeling is an old problem [14]. There are many algorithms used for the computation of the probability of detection of a target in clutter currently used in the literature of image processing and target acquisition modeling. Most are some variation of the Ft. Belvoir , Virginia Night Vision Lab (NVL) model. During the past twenty years there has been an increasing interest in the modeling community to adapt the methods and results of recent research in the area of neurophysiology and human vision research into multiresolution target acquisition modeling [15,16,23]. Presently, target-acquisition-model strategies can be divided into three broad classes:

(1) Computer models that use the "classical" approach to modeling target acquisition performance. These models usually assume a target of uniform contrast to the background. The temperature or luminance of the target is computed by averaging over all the pixels on the target. In these classical models, the target size and contrast are taken as the most important signature parameters for predicting target detectability by observers. This type of model has both IR and visual versions. Signal Detection Theory (SDT) is used with this approach [17] for the computation of Receiver Operator Characteristic (ROC) curves.

(2) Computational models that use the multi-channel and multi-resolution idea carried over from human vision research [24-28] together with signal detection theory concepts from classical psychophysics. The input scene is considered as forming modulated signals that are transduced by the eye and visual cortex to form a mental image from which an observer sees or detects a target. This is the so-called "bottoms-up" approach based on first-principles of human vision and psychophysics. These kinds of computer models are visual models to start, but can be applied to IR scenes since the eye is assumed to look at a displayed image on a monitor [18, 24-28].

(3) Computer models that use neural networks and/or fuzzy logic for predicting detectability based on the input of a data set of target "feature vectors." This type of computer model can be used for both IR and visual images, as well as images from radar and acoustics.

3. FUZZY MODELS

Fuzzy modeling is an approach based on fuzzy logic with fuzzy predicates, using a description language. Zadeh's principle of incompatibility [29] states that "...as the complexity of a system increases, our ability to make precise and yet significant statements about its behavior diminishes, until a threshold is reached beyond which precision and significance (or relevance) become mutually exclusive characteristics."

Fuzzy models basically fall into two categories [30]. The first category, linguistic models, is based on the collection of If-Then rules with vague predicates, and use a fuzzy reasoning such as Mamdani's and Assilian's model [31]. In these models, sets of rules operating with linguistic values of input/output variables, appear as an analogy to the system of equations used for description of linear and non-linear systems. For a Two-Input-Single-Output (TISO) system, the model has the form:

$$\text{If } x \text{ is } A \text{ and } y \text{ is } B \text{ Then } z \text{ is } C \tag{1}$$

Where A, B, and C are fuzzy sets of the universes of discourse X, Y, and Z, respectively.

Sugeno's model [32] is the other category of fuzzy models and they are characterized with functional type conclusions. The Sugeno model for a TISO system:

$$\text{If } x \text{ is } A \text{ and } y \text{ is } B\text{, then } z = f(x, y) \tag{2}$$

where A, and B are fuzzy sets of the universes of discourse X and Y respectively,

and x and y are values of the input variables.

A first-order Sugeno has the form [33],

$$\text{If } x \text{ is } A \text{ and } y \text{ is } B \text{ Then } z = px+qy+r\,. \tag{3}$$

Fuzzy models can be developed using the direct approach, where the model is made directly from an expert's knowledge and expressed in the form of logical rules. The system identification method is another approach [30], which is based on the input-output data using classical system identification techniques and neural networks. This approach may be accomplished using the structure and parameter identifications [32]. The structure identification using Clustering techniques including Fuzzy C-Means (FCM) [34], the Mountain Clustering [35], and the Subtractive Clustering [36] methods; determines input and output variables, relationships between the variables, number of rules, and the partitioning of the input and output variables into fuzzy sets. The parameter identification estimates the MF's of the fuzzy set. More details on the Fuzzy Logic Approach as applied to target acquisition modeling may be found in [19].

4. IMPLEMENTATION

The development of the software package that models the relationship between the various factors that affect the determination of the probability of detection is currently undergoing development. Some of these modeling factors are introduced here to demonstrate the capability of the fuzzy and neuro-fuzzy approaches in predicting Pd with a 0.9 correlation to experimental values as shown in Fig. 2. Tables 1 and 2 show some of the signal, clutter metrics, and the and the signal-to-noise ratio (SNR), and relative SNR's [11] of the target in the foreground of the IR image set of which Fig. 1 is an example. The probability of detection (Pd) value can be determined with the FLA using input parameters for the images shown in Fig. 1 and Fig.'s 3 through 8, the one output parameter is Pd. Fig. 1 is a sample of the infrared terrain board images, from Dr. B. O'Kane at NVESD, used in this study. The terrain and vehicles are scaled models of natural terrain and military ground vehicles. NVESD is the U.S. Army center for research on infrared systems. Fig.'s 3 through 8 are from Dr. Lex Toet of TNO in the Netherlands [37]. TNO is a non-profit research agency the performs human factors research. The figures show a jeep-like vehicle in a field at a distance of around 500 meters. These figures were shown to observers in a perception lab and the observers responses were aggregated to obtain experimental Pd's. For the infrared images, there was enough data to take every other data point and then compare the model predicted Pd to the other set of data points not used in the training. In the case of the visual images, we expanded the dataset of 6 initial images and metrics to 21 sets of metrics by taking averages below and above each individual metric. This expanded dataset was then used as input to the MATLAB Fuzzy Logic Artificial Neural Fuzzy Inference System (ANFIS). The ANFIS (22) uses neural network algorithms to assist in the formation of membership functions and rules thereby saving the user a large amount of time. ANFIS was used to generate the FIS that computed the Pd for each of the images.

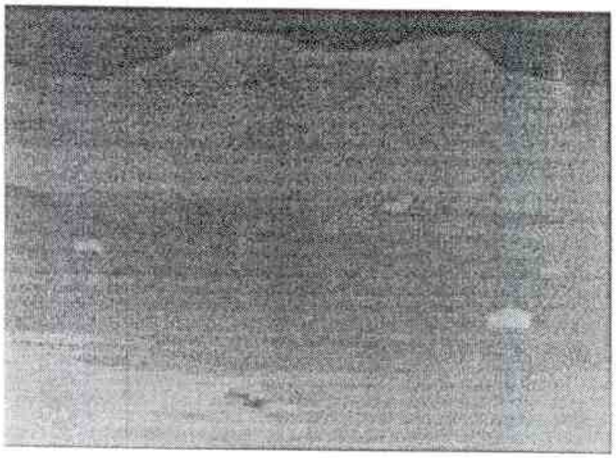

Fig. 1 Night Vision Laboratory Terrain Board thermal image
courtesy of Dr. Barbara. O'Kane

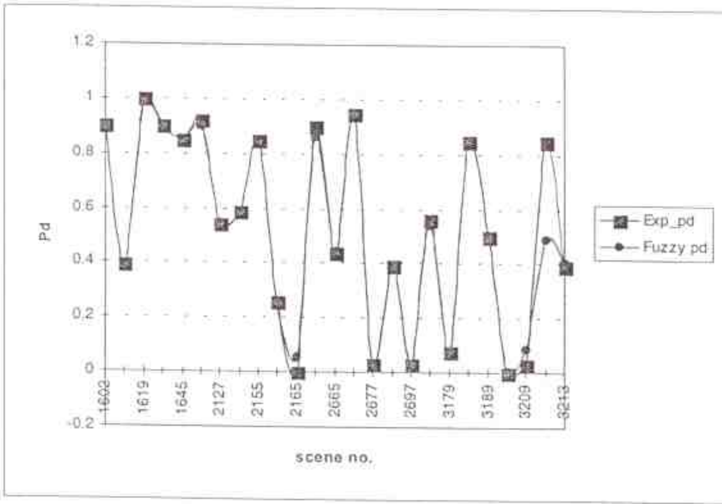

Fig. 2 Experimental vs. Fuzzy Logic Approach predicted Pd for infrared terrain board images

Table 1 Signals for IR images, difference between target and background.

		DT1	DT2	DT3	DT4	DT5	
scenar	pix_avg_dt	rss_dt_deg	doyle_dt	awaa_dt	moulton_dt	Rel_DT	Norm_DT
1607	1.042	1.053	1.047	1.042	4.333	1.488	6.452
1609	-0.142	0.431	0.221	0.142	0.32	-4.63	0.335
1619	0.715	0.891	0.745	0.715	3.237	-0.5	4.461
1645	0.718	0.786	0.718	0.718	3.287	-0.85	4.115
1657	0.395	0.702	0.445	0.395	2.106	-2.58	2.385
2127	1.244	1.263	1.26	1.244	5.119	3.155	8.12
2151	0.625	0.704	0.636	0.625	2.631	-1.68	3.288
2155	0.864	0.886	0.865	0.864	3.334	-0.06	4.902
2159	-0.619	1.049	0.829	0.619	2.631	1.295	6.26
2165	0.233	0.405	0.265	0.233	1.152	-4.47	0.495
2171	1.191	1.261	1.191	1.191	5.279	3.016	7.981
2665	-0.828	1.222	1.072	0.828	3.833	3.64	8.605
2669	-1.488	1.701	1.605	1.488	6.318	9.635	14.6
2677	-0.098	0.473	0.222	0.098	0.406	-4.6	0.363
2691	0.771	0.796	0.776	0.771	3.328	-0.62	4.347
2697	-0.368	0.834	0.416	0.368	2.512	-1.2	3.76
3169	-0.292	1.285	0.987	0.292	1.789	0.937	5.901
3179	-0.379	0.547	0.393	0.379	1.366	-2.61	2.351
3185	-1.175	1.819	1.614	1.175	5.594	8.665	13.63
3189	-0.683	0.767	0.706	0.683	2.772	0.44	5.405
3205	0.417	0.509	0.433	0.417	1.66	-3.37	1.595
3209	0.161	0.405	0.214	0.161	0.499	-4.96	0
3211	1.273	1.338	1.282	1.273	5.709	3.734	8.698
3213	0.096	0.608	0.424	0.096	0.58	-3.86	1.103

Table 2. Noise terms, various clutter metrics and relative SNR of the IR images

der	poe	schmeider	mean_bkg	std_bkg	REL_CLUT	Norm_RCL	REL SNR	Pd-Exp
188	0.001	19.001	3.797	0.251	0.60806	3.85806	2.44647	0.897
174	0.001	19.204	4.353	0.238	-1.5894	1.66057	2.91252	0.385
166	0.003	22.004	2.921	0.323	5.79679	9.04679	-0.0869	1
163	0	15.581	3.62	0.307	0.98251	4.23251	-0.8646	0.846
159	0.004	19.428	2.955	0.375	5.35337	8.60337	-0.4819	0.923
278	0.002	15.743	3.45	0.421	1.35949	4.60949	2.32096	0.538
288	0.003	17.071	3.456	0.204	0.21512	3.46512	-7.7934	0.59
322	0.004	15.204	3.462	0.231	-0.4814	2.76863	0.13096	0.846
334	0.005	15.967	3.707	0.295	-0.9764	2.27365	-1.3267	0.263
334	0.004	15.77	3.584	0.204	-1.1232	2.12684	3.97981	0
333	0.003	15.432	3.388	0.425	1.02421	4.27421	2.94471	0.897
338	0	15.497	3.558	0.218	-1.0928	2.15724	-3.3312	0.385
333	0	16.906	4.146	0.223	-3.058	0.19205	-3.1509	0.436
481	0.008	19.704	3.724	0.264	-1.6176	1.63236	2.84489	0.949
489	0.003	17.695	3.877	0.287	-2.811	0.43896	0.21963	0.026
568	0.005	17.984	3.63	0.553	-0.7379	2.51212	1.63228	0.385
337	0.001	21.859	3.155	0.308	2.96807	6.21807	0.31561	0.026
320	0	17.502	3.803	0.289	-0.9106	2.3394	2.86989	0.564
324	0.001	18.2	3.855	0.283	-0.9965	2.25352	-8.6953	0.077
347	0.001	21.139	4.092	0.169	-2.1237	1.12635	-0.2072	0.846
283	0.001	21.468	3.799	0.176	-0.1358	3.1142	24.8114	0.5
268	0	19.334	4.072	0.231	-1.3753	1.87467	3.60977	0
270	0	19.249	3.31	0.263	1.95249	5.20249	1.91231	0.026
269	0	18.694	3.923	0.187	-1.2307	2.0193	3.13804	0.846

Figures 3 through 8 below show the visual band TNO images used for the FLA approach. The images are of a truck and jeep at a distance of approximately 500 meters at various aspect angles. In some of the pictures the vehicle is partially concealed behind a hill or 'berm' or tree. In Table 3 are listed some of metrics for the Fig.'s 3 through 8. The column labeled Lt/Lb is the target luminance divided by the background luminance which is the effective SNR for these images.

Visual Images

Courtesy of Dr. Lex Toet of TNO

Fig. 3

Fig. 4

Fig. 5

Fig. 6

Fig. 7

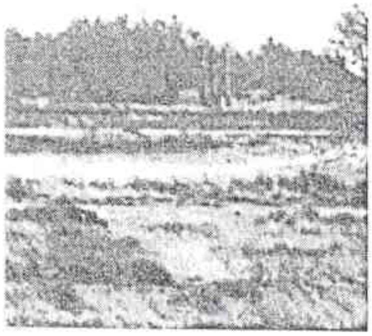

Fig. 8

Table 3 Visual Image metrics and signal to noise ratio (Lt/Lb)

Fig.	view	camou	width	Lt(cd/ m^2)	Lb(cd /m^2)	Lt/Lb	Range (m)	Ct	nrms	Pd
1	f	n	23	4.9	4	1.23	640	9.6	0.53	94.6
2	s	y	34	5.5	4	1.38	500	16	0.45	79.3
3	s	n	40	5.9	3.7	1.59	500	23	0.6	94.9
4	f	n	31	2.5	1.7	1.47	500	19	0.57	96.5
5	s	n	39	4.1	2.4	1.71	945	26	0.33	66.3
6	f	y	29	1.9	1.4	1.36	945	15	0.22	62.7

Below in Fig. 9 is shown the Fuzzy Identification System (FIS) that we constructed in MATLAB with the input parameters mentioned above and the Pd as output. The input parameters are shown on the far left of the figure to be; the width of the vehicle, the target luminance, the background luminance, 'nmrs', which is a texture metric, the distance to the vehicle from the observer, the aspect angle of the vehicle relative to the observer and weather or not the vehicle has camouflage on it. The center block in Fig. 9 shows the type of FIS being constructed, and the box on the far right shows the output variable name. Fig. 10 is the firing array for the various membership functions and can actually be manipulated real time by the user to get a visual feeling for how changing the values of the parameters effects the averaged Pd output. Each column in Fig. 10 represents a parameter, such as target range, and each row represents a group of membership functions. The column on the far right shows the Pd averaged over each membership function.

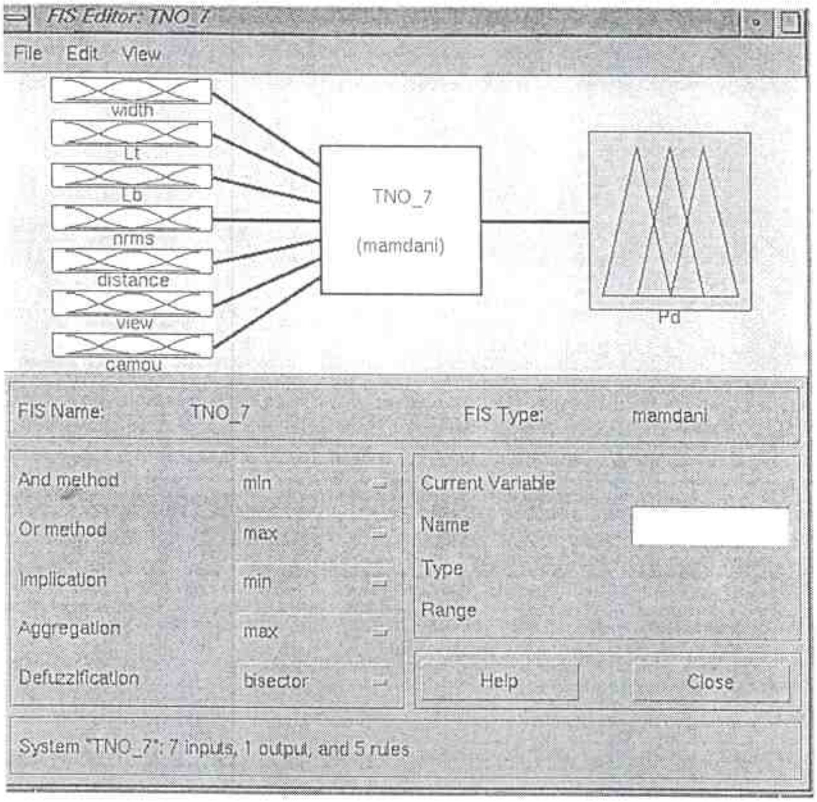

Fig. 9. Fuzzy Logic Identification System for computing visual Pd's

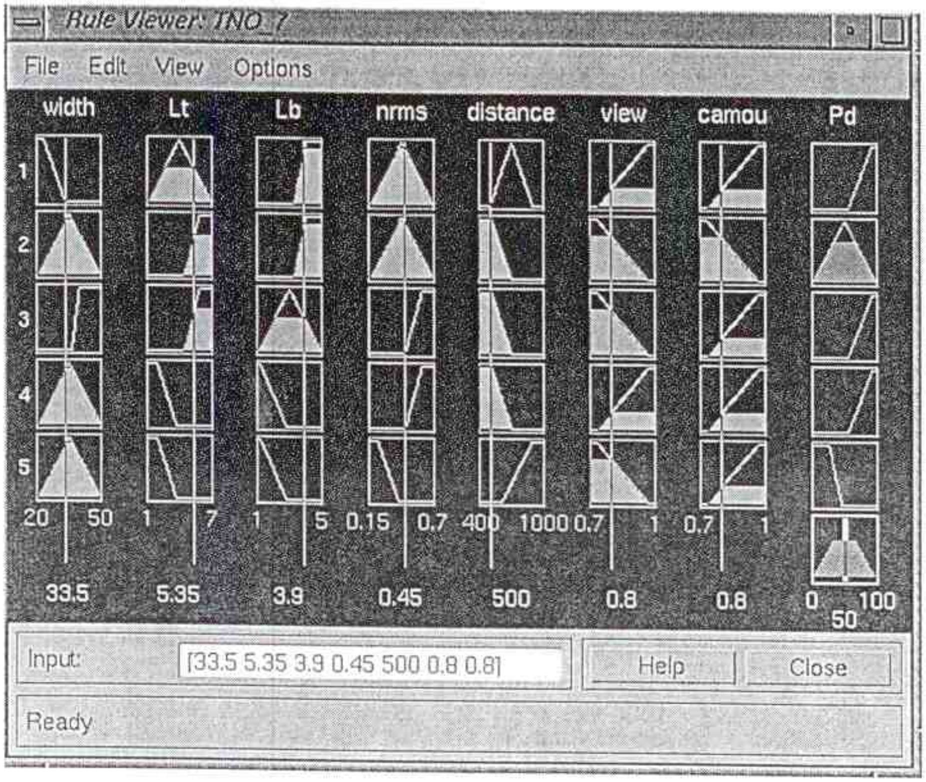

Fig. 10 Firing diagrams for the FIS

5. RESULTS

The percentage Pd's predicted using the Neuro-Fuzzy approach are shown below in Fig. 11. The correlation of the experimental Pd to the FLA predicted Pd was 0.99. What is interesting is that a 0.9 correlation was achieved using an input dataset of only 5 images with seven metrics for each image. This result is indicative of the power of using the FLA to model highly complex data, for which there would be many interrelated equations if one tried to model the detection problem in the standard algorithm based method, in one relatively simple model.

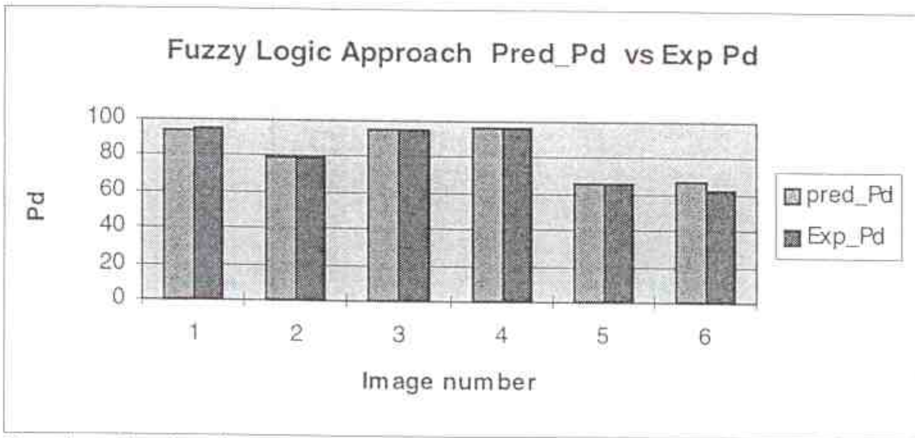

Fig. 11 Bar chart showing the comparison of experimental Pd to FLA predicted Pd for visual images

6. CONCLUSIONS

In conclusion, the FLA yields very satisfactorily results, and requires a fraction of the effort that goes into traditional algorithm based techniques of modeling target acquisition probabilities. Furthermore, fuzzy-based solutions can be created in weeks to months in comparison to the years that may be needed to create a traditional solution. We expect that the fuzzy modeling approach could be used in the statistical decision theory modules of target acquisition models for any spectral regime.

We have developed a prototype software using the fuzzy logic approach. Two fuzzy models have been used: namely the Mamdani and Sugeno models. For the visual image scenarios, using only 5 input-output pairs, we were able to predict the Pd values with a correlation of 0.99 as shown in Fig. 11. A correlation of 0.98 was achieved for the image set of IR images. As shown in Tables 1, 2, and 3, the signal-to-noise level becomes close to zero in many cases and the FLA still produced a model with high correlation.

This application of the FLA involved pictures, metrics, and experimental Pd's taken in the infrared and visual band. Future work will involve the application of the FLA to predict the Pd's of ***moving*** targets in visual and infrared cluttered scenes and the inclusion in the Fuzzy Inference System of multifrequency and color plane information. The membership functions can be designed using experimental Pd's collected in the TARDEC Visual Perception Laboratory (VPL) [23]. As mentioned in [23], the TARDEC VPL is being used in a collaborative R&D project with an auto company on vehicle conspicuity and for various U.S. Army work related to visibility. The lab was recently established and is a 2500 sq. ft. facility that permits embedded simulation. The lab is equipped with state-of-the-art eyetracking and head tracking devices as well as high resolution color projectors. The use of the lab to obtain experimental Pd's is important to the process of building the fuzzy logic models and calibrating other computational vision models that emulate human perception. The more the experimental data available the more robust will be the membership functions. Having a laboratory to perform perception test frees one from the problems with field tests such as, inclement weather and the transportation of equipment. Recently the lab has been used in several instances to collect observer data concerning visibility of various systems.

The FLA can also be applied to detection problems in different energy areas, for instance acoustic energy propagation and material (i.e., metal or semiconductor characterization). The FLA applied to acoustic detection problems will be the topic of a future paper.

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